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Investigating the Factors that Affect the Time of Maximum Rejection Rate of E-waste Using Survival Analysis

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Abstract

This study aims at investigating the factors which influence positively or negatively electronic waste (e-waste) rejection rates. E-waste quantities have been calculated based on historical sales data worldwide and lifespan distribution. The methodology, which is adopted in this paper in order to estimate the effect that economic, cultural, and demographic factors have upon the time at which maximum e-waste rejection is achieved, is a Weibull parametric accelerated failure time model. Considering the event at which the maximum rejection of e-waste takes place as the dependent variable, it is assumed that it is a function of economic (GDP, GINI index, Internet users, exports/imports and prices), demographic (dependency ratio), and cultural covariates (literacy, masculinity, uncertainty avoidance). The variables are fed to the model after transformation into two major constructs derived from Factor Analysis: the first construct is Wealth (exports, imports, and GDP) and the second is Economic Disparity (size of households, literacy, Internet users, and GINI). The results demonstrate that the time of maximum e-waste rejection rate is prolonged by economic disparity and cultural variables (uncertainty avoidance), while wealth causes a shorter time of rejection rate. The proposed methodology is of great value, as its application could provide useful information in order to develop policies for optimal management of e-waste quantities.

Keywords: WEEE, e-waste, e-waste rejection rate, Survival Analysis, Weibull Parametric Accelerated Failure Time model

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1. Introduction

Waste electrical and electronic equipment (WEEE) or electronic waste (e-waste) is a continuously growing problem of the global community. WEEE is a mixture of materials and components of end-of-life electrical and electronic equipment, such as old computers, mobile phones, and kitchen appliances, which, if not properly managed, can cause major environmental and health problems. Due to the current high rates of e-waste generation and rejection, the environment has been dramatically affected; it is a fact that, a radical and immediate solution is required. In recent years, a great effort has been made at global level regarding the management and recycling of e-waste. Unfortunately, this effort is still in its infancy, as only in 2012 the European Union set more stringent conditions for the member states in its directive on WEEE (WEEE Directive 2012/19/EU). This directive was entered into force on 13 August 2012 and became effective on 14 February 2014.

The reasons for the generation of e-waste are composite and include several different factors which contribute positively or negatively to the rate of e-waste rejection. Rejection is considered either recycling or disposal of e-waste in landfills (possibly followed by incineration). Recycling moves hazard materials and components into secondary products that eventually have to be disposed of; thus, recycling is a kind of e-waste rejection practice. Since this study focuses on factors that affect e-waste rejection rates, it should be noted that, from the perspective of a household, the transfer of end-of-life electrical and electronic equipment to a collection point of e-waste is considered a rejection practice, although the owner of the household is not able to know how their e-waste will be finally treated.

E-waste values are calculated based on the product quantities sold and the probability that these quantities will be discarded after the end of their useful life. However, the problem of e-waste does not arise at a discrete point of time, but on a continuous scale. E-waste values do not disappear after some years, but they are added up until the current year. The result of this procedure leads to a cumulative function of: a) computer sales and b) the lifespan probability distribution function (PDF) of computers. The lifespan PDF is a distribution function which provides the probability that a computer will be discarded after the end of its useful life. There are several factors which seem to have impact on e-waste rejection rates, but yet they have not been examined in the literature. Generally, the factors that affect e-waste rejection

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rates are divided into three main categories, namely, economic, demographic, and individual preferences and awareness. Let us see some indicative factors from each category. The income, for instance, is one of the significant economic factors since higher income people tend to buy more and often contemporary Information Technology (IT) equipment replacing old devices. Usually, the useful life of the devices that are replaced has not been expired. The level of education is a demographic factor which also affects e-waste rejection rate. More educated people use modern IT equipment to a greater extent than people of low education, and as a result, they dispose of old devices more often. It should also be noted that more educated people are usually more sensitive concerning environmental issues. The extent, to which someone is aware of the seriousness of e-waste rejection or recycling, influences the rejection rates as well.

This paper provides a framework for identifying the factors, qualitative and quantitative, that affect the maximum e-waste rejection rate. Data for other factors could be fed into the proposed model generating information that could be useful to governmental authorities and environmental agencies in the context of: *a*) computing the time of maximum e-waste rejection rate and *b*) understanding the reasons which accelerate or decelerate the speed, at which the maximum rate will be reached. Using this information, corresponding frameworks and policies could be created for optimal management and treatment of e-waste. The significance of the model and the presented results are crucial for determining how e-waste management operations can be sustainable.

The rest of the paper is organized as follows: in Section 2, a comprehensive literature review is presented, identifying the direction to which the examined factors affect the rejection rate. In Section 3, the proposed methodology is described while the results are presented in Section 4. A discussion of the paper is provided in Section 5 and a decision problem example is mentioned in Section 6. The policy implications of our study are given in Section 7 and finally the conclusions of this study are summarized in Section 8.

2. Literature review

As already mentioned, there are a number of different factors that have significant impact on e-waste rejection rate. However, these factors have been considered in the

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extant literature individually and not as a whole of concrete factors with a known and measurable impact. The literature gap that has been the motivation for the current study is that the direction and the extent of impact of all these factors upon e-waste rejection rate have not been adequately examined. It should be noted that the bridging of this gap could assist in analyzing, not only the behavior of users with regard to e-waste treatment and forecasting, but also in estimating the time of maximum rejection rates in order to plan and schedule the appropriate methods and means of e-waste collection.

In the following lines, a list of selected studies and researches of how specific factors influence the rejection rates of e-waste is provided. The literature review has been expanded to economic and demographic factors that are related to any type of waste since an exclusive review for e-waste would not result in a satisfactory number of works. The factors that have been mostly examined in the literature are the following: (i) income and GDP, (ii) household size, (iii) age, (iv) gender, and (v) level of education. As it was expected, many studies have focused on the economic factors (GDP, income, etc.). It is a fact that, income is a significant factor analyzed in a lot of papers, which concluded that waste rejection of households increases when there is a growth in income (Afroz, Hanaki, & Tuddin, 2010; Bandara, Hettiaratchi, Wirasinghe, & Pilapiiya, 2007; Fiorillo, 2013; Gorecki, Acheson, & Lyons, 2010; Hong, Adams, & Love, 1993; Jenkins, Martinez, Palmer, & Podolsky, 2003; Mazzanti & Zoboli, 2009). Other studies claim that the household size influences waste rejection with larger families producing in total greater quantity than smaller families (Afroz et al., 2010; Bandara et al., 2007; Gorecki et al., 2010; Monavari, Omrani, Karbassi, & Raof, 2012). In another study, it was found that women are more likely to recycle their waste compared to men (Saphores, Nixon, Ogunseitan, & Shapiro, 2009). It has been claimed that the level of education is not relevant with the waste rejection level, but several studies showed that, the higher the education level the higher the waste rejection (e.g. Folz & Giles, 2002). Moreover, there have been many studies concluding that the imposition of various types of waste charges (volume-based, weight-based, etc.) reduces the amount of household waste (Allers & Hoeben, 2010; Dahlén & Lagerkvist, 2010; Folz & Giles, 2002; Fullerton & Kinnaman, 1996; Gorecki et al., 2010; O'Callaghan-Platt & Davies, 2007). Colesca, Ciocoiu, & Popescu (2014) indicate that there is a relation between WEEE and age, education, and income, while gender and household size have not been found to be

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relevant. Researchers also support that socio-demographic factors, such as gender, age, education, location, family income, and even ethnicity or political ideology are important to characterize the recycling behavior (Berger, 1997; Knussen, Yule, MacKenzie, & Wells, 2004; Martin, Williams, & Clark, 2006; Owens, Dickerson, & Macintosh, 2000; Vicente & Reis, 2007).

In addition to the above, it should be noted that survival analysis has been used in the discipline of economics (especially banking) as duration analysis (Gutiérrez & Lozano, 2012; Ho Ha & Krishnan, 2012). Besides statistical analysis, Petri Nets (PN) have also been examined for the disassembly and recycling of end-of-life electrical and electronic products (Kuo, 2013).

A summary of our literature review is presented in Table 1, indicating the effect of important factors upon waste rejection rate. As it can be seen in the table, income – GDP, household size, and education level have a positive effect upon waste rejection rate, while gender (male) and age have a negative effect.

Table 1: Impact of economic and demographic factors upon waste rejection

Authors / year	**Income - GDP**	**Household Size**	**Age**	**Gender (Male)**	**Level of Education**	**Methodology**	**Country**
(Afroz et al., 2010)	+	+				Regression model	Bangladesh
(Allers & Hoeben, 2010)	?					Ordinary least squares	Netherlands
(Bandara et al., 2007)	+	+				Regression analysis	Sri Lanka
(Berger, 1997)	+	+	–	–	+	Regression analysis	Canada
(Colesca et al., 2014)	+	?	–	?	+	Fuzzy model	Romania
(Dahlén & Lagerkvist, 2010)	+					Through questionnaire	Sweden
(Fiorillo, 2013)	+					Personal interviews – econometrical analysis	Italy
(Folz & Giles, 2002)					+	Survey & logistic regression estimates	USA
(Fullerton & Kinnaman, 1996)	–					Based on the data of a program implemented in Virginia	USA
(Gorecki et al., 2010)	+	+				Cost-benefit analysis & strategic environmental assessment	Ireland
(Hong et al.,	+					Regression	USA

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1993)						analysis	
(Jenkins et al., 2003)	+					Survey in 20 US metropolitan areas – Regression model	USA
(Knussen et al., 2004)			–	–	+	Through questionnaire	Scotland, UK
(Martin et al., 2006)		+				Through questionnaire, group interviews, and focus groups	England, UK
(Mazzanti & Zoboli, 2009)	+	+				Regression model	25 European Union countries
(Monavari et al., 2012)		+	–		+	Field survey	Iran
(O'Callaghan-Platt & Davies, 2007)	?					Telephone and email surveys	Ireland
(Owens et al., 2000)	+	+	–	–	+	Based on a stratified random sample of residences	Georgia, USA
(Palatnik, Brody, Ayalon, & Shechter, 2014)	+	+				Regression analysis	A number of OECD countries
(Saphores et al., 2009)	+			–	+	Internet-based survey	USA
(Scott & Watson, 2006)	+	+			+	Interviews with households	Ireland
(Vicente & Reis, 2007)		+	–	–	+	Interviews with households – Principal components analysis	Portugal

(+) Positive impact, (-) Negative impact, (?) Direction of impact is not clear and needs further investigation

3. Methodology

The methodology of this study is segregated into three consecutive parts: in the first one, the research hypotheses are formulated; the second part includes the calculation of e-waste quantities over a time horizon (1984 – 2012) and following that, the maximum rejection rate is calculated based on the distribution function of e-waste quantities. Finally, the third part deals with the investigation of the impact of specific factors (the factors considered herein are economic, demographic, and cultural) upon the time, at which the maximum e-waste rejection rate takes place.

3.1 Research hypotheses

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Based on the knowledge derived from the literature review, the following research hypotheses are formulated:

Research hypothesis H1: "*Economic factors affect positively e-waste rejection rate*"

"Economic factors" is a latent construct that consists of GDP, imports/exports, prices, and GINI index (or coefficient). The GINI index is a measure of inequality in the wealth distribution of a country. The range of GINI index is [0, 1]. As *GINI* index expresses a ratio, the numerator is the area between the *Lorenz* curve of the distribution and the uniform distribution line; the denominator is the area under the uniform distribution line. Data for GINI indices for every country in this study have been collected from the *Euromonitor* database (Kotabe, 2002; Hines, 2006). According to the literature review, an increase in income and consequently in GDP has a resulting increase in e-waste rejection rate. As the consumer's expenditure grows (because their income increases), the quantity of IT products that are bought is larger, leading to an increase of e-waste quantity. On the other hand, lower income people are more likely to extend the life of their products, leading to lower e-waste rejection rate. Moreover, as GDP is not independent to other economic activities, imports and exports are also considered as economic factors that affect positively e-waste rejection rate.

Research hypothesis H2: "*Prices and GINI index affect negatively e-waste rejection rate*"

The two sub-factors of the economic construct, namely, prices and GINI index affect negatively e-waste rejection rate. As mentioned above, the GINI index measures the distribution of income (or consumption expenditure) providing a figure for the deviation from equal distribution. Thus, as the value of the GINI index in a country increases, the rejection rate of e-waste decreases as people are more reluctant to consider a computer as obsolete, due to the fact that their purchasing power has diminished. The negative effect of prices on e-waste rejection rate is straightforward; the higher the price of equipment (e.g. computers, tablets, mobile devices), the less the probability that someone will dispose of it.

Research hypothesis H3: "*Household size affects positively e-waste rejection rate*"

An increase in the household size leads to an increase in e-waste rejection. That happens because the more people in a household, the more waste (in all categories) they produce and reject.

Research hypothesis H4: "*Age affects negatively e-waste rejection rate*"

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Younger people usually reject more waste in all categories, and particularly in the category of IT equipment. This is due to the fact that younger people tend to buy newer equipment more often than older people. Besides, they tend to replace their IT equipment in a shorter time period and consequently they reject more e-waste.

Research hypothesis H5: "*Gender is a factor that affects e-waste rejection rate*"

Generally, men reject and recycle less than women. The reason is that women usually do most of the housework, and therefore their participation in waste rejection and recycling is higher than men.

Research hypothesis H6: "*Education level affects positively e-waste rejection rate*"

As it is stated in hypothesis H6, the higher education level leads to higher e-waste rejection rate. The reason is that people with higher education level are more likely to work in professions with higher requirements in IT equipment, and consequently they will use similar equipment in their daily life. It is also a matter of culture since more educated people are also more cultured with a higher degree of sensitiveness in the issues of waste rejection and recycling.

3.2 E-waste generation calculation

E-waste is defined as obsolete computers, their peripherals, and other IT devices that are not in use anymore (there are several categories of electrical and electronic equipment, but this study focuses on computers and peripherals). The estimation of e-waste quantities is based on two components: (i) sales of the corresponding computers and peripherals and (ii) lifespan empirical distribution function (Petridis, Stiakakis, Petridis, & Dey, 2016). Lifespan distribution is the probability at which quantities will be rejected in a specific time period (e.g. in the next 3 years). Based on the above two components, Yu, Williams, Ju, & Yang (2010) have introduced the following equation:

$$O_i\left(t\right) = \sum_{j<t} S_i\left(t-j\right) \cdot L_i\left(j\right) \tag{1}$$

In equation (1), variable $O_i\left(t\right)$ stands for the obsolete computer and peripheral quantities (e-waste) that are produced in country i at time period t. $S_i\left(t\right)$ represents the computer and peripheral sales in country i at time period t and $L_i\left(j\right)$ is the

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empirical probability density function, such that in time period j $(j < t)$, sales of computer and peripheral quantities are considered as obsolete. The distribution of obsolete PC quantities, which is used in this study, is derived by the first order differences of obsolete PC quantities (derived from equation 1). The first order differences of PC obsolete quantities in time points t and $t-1$ for each country i are denoted with $\Delta O_i(t)$ and calculation is given below:

$$\Delta O_i(t) = O_i(t) - O_i(t-1), \; t > 2, \; \forall i \quad (2)$$

The known distributions for modeling lifespan are Normal, Weibull, Log Normal, Cauchy, Logistic, and Exponential. The probability density functions (PDFs) of these distributions are presented in Table 2. Lifespan distribution functions were analyzed for major regions, namely, Western and Eastern Europe, North and South/Middle America, Australia/New Zealand/Japan, and Asia/Pacific. E-waste quantities are calculated for the countries that belong to the aforementioned regions based on sales data and lifespan PDF. The leading countries that have been considered for the analysis from each region are given below:

- Western Europe: France, United Kingdom, Germany, Denmark, Italy, Norway, Sweden, Finland
- Eastern Europe: Greece, Poland, Hungary, Czech Republic, Bulgaria, Estonia, Lithuania, Latvia, Slovakia
- Asia/Pacific: Hong Kong, Singapore, South Korea, Iran, China, Indonesia, Malaysia, Taiwan
- Japan, Australia, New Zealand
- North America: Canada, USA
- Middle/South America: Mexico, Uruguay, Argentina, Brazil.

The selection of the countries in the sample was based on the fact that they are representative countries in their regions in terms of GDP, welfare, population size, and growth, for the time period selected (1984 – 2012). The possibility to have other representative countries for each region was hindered due to unavailability of PC sales data for the specific time period in the *Euromonitor* database.

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Table 2: The examined Probability Density Functions (PDFs)

Distribution	PDF
Normal	$f\left(t;\mu,\sigma\right)=\frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{(t-\mu)^2}{2\sigma^2}}$
Weibull	$f\left(t;\lambda,k\right)=\frac{k}{\lambda}\left(\frac{t}{\lambda}\right)^k e^{-\left(\frac{t}{\lambda}\right)^k}$
Log-Normal	$f\left(t;\mu,\sigma\right)=\frac{1}{t\cdot\sigma\cdot\sqrt{2\pi}}e^{-\frac{(\ln(t)-\mu)^2}{2\cdot\sigma^2}}$
Cauchy	$f\left(t;0,1\right)=\frac{1}{\pi\cdot\left(1+t^2\right)}$
Logistic	$f\left(t;\mu,\sigma\right)=\frac{e^{-\frac{t-\mu}{\sigma}}}{\sigma\cdot\left(1+e^{-\frac{t-\mu}{\sigma}}\right)}$
Exponential	$f\left(t;\lambda\right)=\lambda\cdot e^{-\lambda\cdot t}$

Using Maximum Likelihood Estimation (MLE) method, BIC and AIC indices as distribution fitting tests[2], the most suitable distribution has been selected as lifespan PDF for each region. The results regarding the parameters for the distribution of lifespan for each of the examined regions are presented in Table 3 (as investigated in Petridis et al., 2016).

Table 3: Parameters of the fitted distributions for all regions

	Distribution Parameters		
Region	**Shape (λ)**	**Scale (k)**	**PDF**
Western Europe	7.412	4.758	**Weibull**
Eastern Europe	6.056	5.231	
North America	3.813	4.260	
South/Middle America	6.538	5.785	
Japan, Australia, New Zealand	6.186	4.754	
	Mean (μ)	**Standard Deviation (σ)**	
Asia/Pacific	4.929	0.698	**Normal**

[2] The fitting indices used are calculated using *fitdistrplus* R-package

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3.2.1 An illustrative example

Initially cumulative obsolete quantities for each country are calculated using equation (1). Applying this formula to the observed data (PC sales), series of PC obsolete quantities are created. A consideration of cumulative obsolete PC quantities is erroneous, due to the fact that the time point, at which maximum rejection rate occurs, would always be the last year because of maximum quantities reported. Instead, first order differences ($O_i(t) - O_i(t-1)$) are calculated to identify the real maximum rejection rate time point using equation (2).

Let us consider the case of China. In Figure 1, the time series of obsolete quantities are presented. In 2004, the maximum amount of PC quantities was rejected according to equation (2). Given that the available data for obsolete quantities for the case of China span from 1984 up to 2012, the event (maximum rejection quantity) takes place at the 21st time point (vertical solid line).

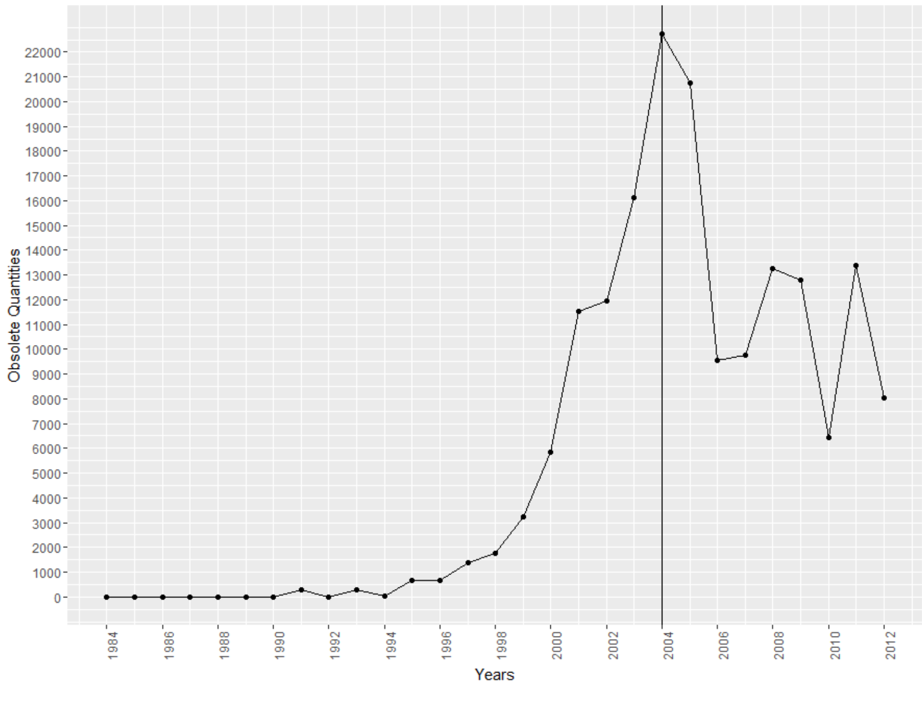

Figure 1 Obsolete quantities for the case of China

Due to the fact that for sales data in many geographical regions, Weibull distribution fits better than Normal distribution, this time does not correspond to the mean time. It is well known that Weibull's PDF exhibits heavy skewness (usually positive), which is strongly dependent on the value of shape (λ) and scale (k) parameters. In geographic regions, in which Normal distribution fits better to the data compared to

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Weibull, this time indeed corresponds to the mean time. However, this cannot be generalized for all countries in the sample of this study.

3.3 Description of data

The data, which are used as explanatory variables in the Weibull AFT model, were collected from various statistical databases (i.e. World Bank, Penn World Tables, OECD reports, and others) and span from 1984 up to 2012. GDP is measured in million US $ in 2000 constant prices, while data for Exports and Imports concern million US $ in current prices and include all goods leaving the economic territory of a compiling country, valued at FOB (free on board price) and CIF (cost, insurance, and freight) prices.

In order the effect that prices have on probability of the event (maximum rejection rate of PC quantities) to be investigated, the consumer Price index (using 1995 as base year) is used. This measure changes over time in the general level of prices of goods and services that a reference population acquires, uses or pays for consumption.

GINI index, on the other hand, is used in order to measure the economic inequality among the members of a society. Its calculation is based on a *Lorenz* curve; values of GINI coefficient close to 0 indicate perfect equality, while values which tend to unity imply strong economic disparity.

The amount of Internet Users refers to all the residents older than 5 years old, who have access to the Internet at home, working place or even Internet cafés. Literacy is measured as the number of higher education students (including universities) in thousand students.

The age is defined as the sum of the percentages of people who are up to 14 years old plus those who are 65 years old and over, to the percentage of people who are between 15 and 64 years old. This composite variable is named as Dependency Ratio. The Gender variable refers to the number of males as percentage of the total population. Households refer to the number of households in each country.

The Uncertainty Avoidance Index (UAI) and Masculinity (MAS) cultural dimensions were obtained from Hofstede (Hofstede & Bond, 1984). Uncertainty avoidance measures the degree, to which the members of a society seek stability and a peaceful way of living, while dislike taking risks. Masculinity is defined as the extent to which the members of a society present male characteristics; these are tendency for

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distinction, demonstration of heroism, and lack of caring. Mean values of the variables used, on country level, are provided in Table I (Appendix). Correlations of the variables are presented in Table II (Appendix), while descriptive statistics for the variables of the study are provided in Table III (Appendix).

Based on the correlation matrix (Table II, Appendix), the highest positive correlation (0.94) is presented between variables Imports and Exports, while the second larger correlation between Imports and GDP. On the contrary, variables Dependency Ratio and Exports seem to move into different directions since a weak negative correlation is reported (-0.18) and the same is reported between the number of Households and UAI. The values were calculated for the time horizon 1984 – 2012.

3.4 Maximum rejection rate analysis

In this section, the accelerated failure time models (AFT) assuming Weibull distribution is described. The dependent variable in this study is the time at which the maximum rejection time takes place in each country of the sample (T_i). As presented in Section 2, the time at which the event takes place is considered to be a function of economic, demographic and cultural characteristics of each country. The equation, which describes the relationship between dependent and independent variables, is the following:

$$Y_i = \log(T_i) = X\beta + \sigma\varepsilon \tag{3}$$

where X is the matrix of the independent variables, β the vector of parameters to be estimated using MLE method, σ denotes the unknown scale parameter and ε the vector of residuals.

The hazard function is defined as the likelihood that the maximum rejection time may not occur in the interval $[0,t]$ which in a more general formulation can be expressed as (Nelson, 2005):

$$h(t) = \frac{f(t)}{1-F(t)} \tag{4}$$

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where $f(t)$ is the probability density function and $F(t)$ the cumulative density function. Specifically, the hazard function for Weibull AFT models is given as:

$$h(t) = \lambda \cdot p \cdot t^{p-1} \tag{5}$$

The denominator of equation (4) presents the survival function, namely, $S(t) = 1 - F(t)$ and under the assumption that duration time until maximum e-waste quantity is rejected, is Weibull distributed given that $X(t_i)$ denotes the value of explanatory variable at time point t_i, the survival function becomes:

$$S(t_i \mid X(t_i)] = e^{-\int_0^{t_1} h(s|X(0)ds} \times ... \times e^{-\int_{t_{n-1}}^{t_n} h(s|X(t_{n-1})ds} = e^{-\sum_{i=1}^{n} \int_{t_{i-1}}^{t_i} h(s|X(t_{i-1})ds} \tag{6}$$

Weibull AFT model is the most appropriate, if independent variables contain time – varying and time invariant covariates, which are associated with the interpretation of year at which maximum e-waste rejection takes place (Therneau & Lumley, 2010; Helsen & Schmittlein, 1993).

The technique works as follows; initially, the time at which the event takes place is estimated (T^*). Event is a binary variable taking value 1 if the event is observed before T ($T^* \leq T$) and 0 otherwise. Therefore, the observations are censored for every time period which exceeds T^*. The procedure is graphically illustrated in Figure 2. For example, let the distribution of obsolete PC quantities be *f*(t) and T^* corresponds to time where rejection rate becomes maximum (as it can be seen from distribution). Let *X* be an independent variable which is associated with the time of maximum rejection rate (e.g. GDP). Variable *X* spans from t_0 to T. However, values of variable *X* before T^* are taken into account concerning the analysis, while values for time after T^* are not used at all. Consequently, the analysis of the effect that covariates have on the time at which maximum rejection rates occurs, is based on observations which span from t_0 until the time the event took place (T^*). As several countries are examined,

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the event takes place in different time points for each country *i*. Therefore, the time of the event is defined as T_i^*.

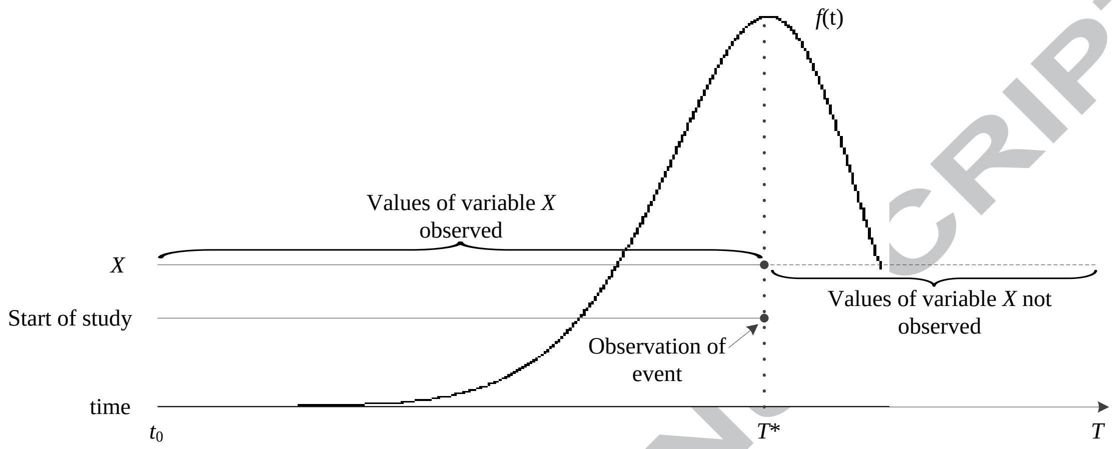

Figure 2 Graphical explanation of observations' censoring

The goodness of fit of the Weibull AFT (Kalbfleisch & Prentice, 2011) model is evaluated using McFadden's pseudo – R squared, which is often called as Likelihood Ratio Index or LRI (McFadden, 1976). Let LL_0 be the value of Weibull AFT's log - likelihood function without any explanatory variables and $LL_{\hat{b}}$ the value of Weibull AFT's log – likelihood function having been estimated using all the independent variables, the McFadden's R – squared index is defined as:

$$R^2 = 1 - \frac{LL_{\hat{b}}}{LL_0} \quad (7)$$

McFadden's R – squared values which lie into the interval 0.2 (20%) to 0.4 (40%) signal excellent fit for a binary discrete choice logistic model (McFadden, 1977).

4. Results

4.1 Descriptive statistics

Table 4 illustrates the descriptive statistics of the time at which maximum e-waste rejection takes place, according to the geographical continent to which each country in the sample belongs. In South America, it is observed a very prolonged period (33 years) by which PC quantities become obsolete and are transformed to e-waste.

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Consumers in Oceania – Japan, North America, and Central – East Asia tend to preserve PCs on average 25 years, while in Eastern Europe the time by which PC systems are substituted, rejected or recycled reaches almost 29 years. Consumers in countries, which geographically belong to Western Europe, tend to discard PCs much earlier (23.78 years). The maximum rejection time of PC quantities is on average 26.27 years for all the countries, which were included in the sample of this research.

Table 4: Descriptive statistics for time of maximum rejection per geographic region

Geographic Region	Mean time	SD of time
South America	33.00	1.00
Oceania - Japan	24.67	3.51
North America	25.00	5.29
Eastern Europe	28.63	1.68
Western Europe	23.78	3.38
Central and East Asia	25.14	4.88
Overall	**26.27**	**4.31**

It is obvious that the time by which PCs become obsolete varies considerably across different countries ($F(5,27) = 4.13$, $p < 0.01$); however, in countries which are adjacent or have a lot of characteristics in common, such as economic growth, culture, religion, language or demographic variables, the time is approximately the same. In Figure 3, the survival curves, which were estimated separately for each geographic region, are presented. These curves depict the probability for each year that the time at which maximum rejection e-waste quantity takes place. In Western Europe, there is approximately 75% probability that maximum rejection of PCs takes place during the 25th year, while for the same probability in South America, the time at which PC quantity reaches maximum, is almost 34 years. The fact that survival curves confirm the results, which are presented in Figure 3 and Table 7, indicates exceptional fit to the data.

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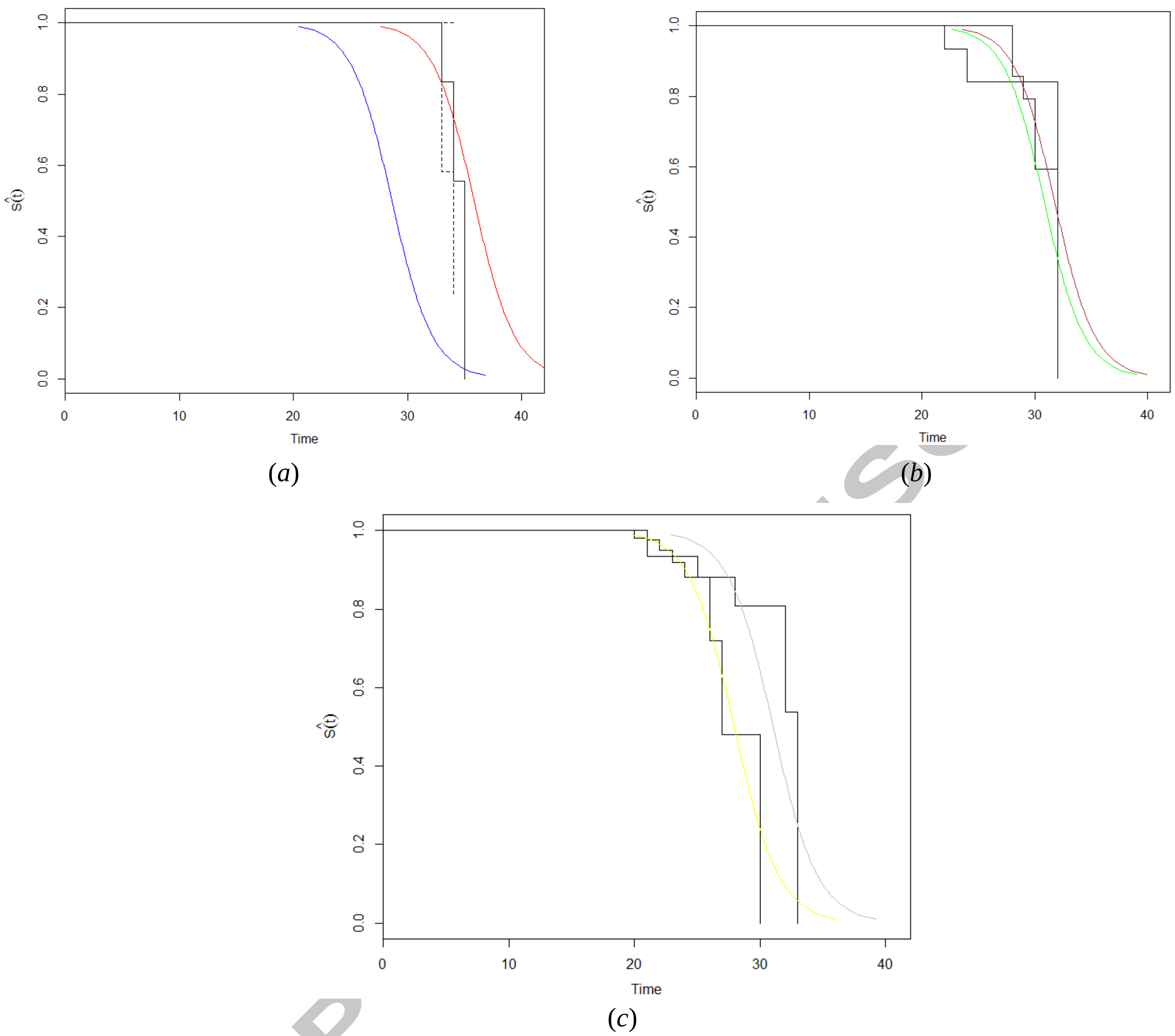

Figure 3 Survival curves for each continent, (*a*) blue - Oceania and Japan, red - South America, (*b*) green - North America, brown - Eastern Europe, (*c*) yellow - Western Europe, gray - Central and East Asia

4.2 Univariate Weibull AFT

In Table 5, the estimates of Weibull AFT model are presented. Positive beta (β) coefficients indicate that the independent variable causes time at which maximum rejection of e-waste to be prolonged, while negative betas demonstrate that covariates affect positively the probability that the event takes place sooner.

As expected, GDP of a country is a factor which leads to shorter time for maximum e-waste rejected PC quantity, due to the fact that its coefficient is negative and statistically significant ($\beta = -0.27$, $p < 0.01$). This actually means that the time at which the event occurs is declining over increased GDP (rich countries) rather than poor countries. Furthermore, trade is another explanatory variable which leads to

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decreased time at which maximum rejection of PC quantities takes place. Specifically, exports increase the probability that maximum rejection occurs sooner by 0.35, while imports tend to have the same effect by approximately the same amount (β = -0.29, p < 0.01). Both coefficients have the expected sign and are statistically different from zero.

On the other hand, in countries with high income inequality (GINI) among their members, the time, at which the maximum rejection of PCs takes place, is increasing (β = 0.49, p < 0.01). The consumer price index (Prices) has the same effect on the time at which the event occurs. The coefficient indicates that in a country whose price level is increasing, the time at which maximum rejection takes place is increasing, as well (β = 0.66, p < 0.01).

The amount of male population is associated with increased time at which maximum rejection time takes place. The coefficient is consistent with the research hypothesis, although it is not statistically significant. On the other hand, the age of the population in a country is also found to have a positive effect on delaying recycling or rejection of e-waste (β = 0.85, p < 0.01). This finding is consistent with the research hypotheses which were set earlier. The last independent variable, which is included in the construct of demographic factors, is the literacy level. As expected, the more literate the individuals are, the more they will participate in e-waste rejection, and thus the time at which maximum PC turns into e-waste becomes shorter. The estimated coefficient of literacy neither has the expected sign nor is statistically significant. The last demographic factor examined is the size of the households. The impact that the number of people who live in a household has on their decision to recycle is overall positive. Therefore, the larger the household is, the more the time, at which maximum quantity of PCs is rejected, is declining. The estimated coefficient is consistent with the research hypothesis, although it is not statistically significant.

Except for the covariates which have been used so far in the context of the factors which affect e-waste generation, two additional explanatory variables are included and tested. These variables compose the cultural dimension which may affect the time at which maximum rejection takes place; to our knowledge, this is the first work that studies the effect of these variables. For that reason, the direction of the causal relationship is unknown. However, societies which are high in uncertainty avoidance tend to reject e-waste later compared to countries which are low in taking risks (β = 0.45, p < 0.01). The same effect seems to have the cultural dimension masculinity on

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the time at which rejection of maximum quantity occurs. In countries, which are characterized by large masculinity, the time, at which the event occurs, is increased.

Table 5: Estimates of univariate Weibull AFT models

	Expected sign	Betas	Wald Statistic	R^2
Economy				
GDP	(+)	-0.27	-3.06^{***}	0.09
Exports	(+)	-0.35	-3.29^{***}	0.14
Imports	(+)	-0.29	-4.11^{***}	0.17
Internet users	(?)	0.26	$0.27^{n.\ s.}$	0.00
GINI	(-)	0.49	2.68^{***}	0.11
Prices	(-)	0.66	3.44^{***}	0.12
Demographics				
Dependency ratio	(-)	0.63	2.11^{**}	0.09
Gender	(-)	-0.18	$-0.12^{n.s}$	0.00
Literacy	(+)	0.03	$0.44^{n.s}$	0.00
Households	(+)	-0.86	-3.76^{***}	0.22
Culture				
Uncertainty avoidance	(?)	0.33	4.21^{***}	0.26
Masculinity	(?)	0.02	$0.14^{n.\ s.}$	0.00

***:p – value < 0.01, **:p – value < 0.05, *:p – value < 0.1, $^{n.s.}$: not significant

4.3 Factor Analysis

In Table 5 univariate models are estimated, due to the fact that most of the explanatory variables are heavily correlated and should this fact be ignored, leads to *multicollinearity*. In case where the correlation structure between independent variables is ignored, and a multivariate model is estimated (Wooldridge, 2012; Greene, 2003), then:

a) Standard errors will be inflated, result of which will be the absence of statistically significant effects,
b) Coefficients tend to change their signs when the model is estimated using different random samples. This instability of coefficients is a consequence of multicollinearity existence, and
c) The collinear variables contain the same information about the dependent variable, which leads to a non – parsimonious model.

<u>*Definition of Multicollinearity*</u>

Let $\mathbf{X}$ be a matrix of independent variables of dimension $n \times (k+1)$, where n is the number of observations and k the number of independent variables used in estimation.

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If $\mathbf{X}$ is not of full rank, this means that $\left|\mathbf{X}^{'}\mathbf{X}\right| = 0$, and therefore some columns (variables) can be expressed as a linear combination of others (e.g. Greene, 2003). This actually leads to infeasibility of estimation, even if this is done via Maximum Likelihood.

Remedy for Multicollinearity

A way to reduce multicollinearity, for a given dataset, is to drop independent variables (Wooldridge, 2015, p. 96). Though this solution is acknowledged, it would limit the analysis of this study and therefore, some research hypotheses could not be tested. To overcome this obstacle, a standard procedure to deal with heavily correlated covariates is the implementation of Explanatory Factor Analysis (EFA) or Principal Component Analysis (PCA) (Farrar & Glauber, 1967). The result of EFA (or PCA) implementation is the creation of uncorrelated (orthogonal) factor scores (usually Bartlett scores are chosen), which can be included simultaneously in the Weibull Accelerated Failure Time models.

Table 6: Factor analysis of independent variables

	Wealth	**Economic Disparity**
Imports	**1.02**	-0.05
Exports	**0.95**	-0.02
GDP	**0.79**	0.16
Household	-0.13	**0.91**
Literacy	0.18	**0.86**
Internet Users	0.46	**0.50**
GINI	-0.01	**0.34**
Prices	-0.25	0.22
% of variance explained	**0.39**	**0.28**

The factors were extracted[3] using Oblimin method and they were rotated using Varimax procedure. Based on the largest eigenvalue, the optimal number of factors which will be constructed is 2 (Table 6). The first factor which is named after *Wealth* (39% of variance explained) contains GDP, imports, and exports, while the second factor, *Economic Disparity* (28% of variance explained) includes the Internet users, the size of households, country's literacy level, and GINI index. In addition, prices do not load highly on any of the two factors created and consequently this variable is excluded from further analysis.

[3] The factor analysis was performed in R (CRAN) using *fa* function from psych library (Revelle, 2013)

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4.4 Multivariate Weibull AFT model

In Table 7, the estimates of Weibull incorporating explanatory variables, as well as the constructed factors, are presented. The factor of countries' wealth is associated with decreasing time at which the event takes place, as expected and is statistically significant ($\beta = -0.44$, $p < 0.01$).

The construct media intensity which includes the amount of Internet users in a country along with the household size has also been found to be statistically significant. Although, countries which are high in media intensity tend to experience prolonged times of maximum PC rejection quantities. This finding is contradictory, due to the fact that the covariates which compose this composite variable are assumed to be associated with shorter times of maximum e-waste rejection. On the other hand, in this research the univariate models which included Internet users and size of households separately were not statistically significant and therefore no assumption can be set about the higher order construct (economic disparity) ($\beta = 0.01$, $p < 0.05$).

Societies which are high in uncertainty avoidance tend to reject PC quantities later than societies which are low in it ($\beta = 0.33$, $p < 0.01$). The coefficient is consistent with the univariate analysis. This finding makes sense due to the fact that individuals which avoid taking risks are more conservative and have a hostile attitude towards anything innovative. Therefore, they will not take chances rejecting a device which they possess, before being sure about the functionality and their practical utility.

Countries which are high in masculinity tend to reject PC devices earlier compared to countries which are high in feminity. However, the coefficient is not statistically significant and consequently no result can be certainly drawn about the impact that this explanatory variable has on time at which the event takes place.

As far as the demographic variables are concerned, the amount of male residents is associated with prolonged time at which maximum rejection of PCs takes place; however, the coefficient is not statistically significant. The age of a country's population is another deterrent factor which prevents the quick substitution of PC devices. The model exhibits exceptional fit to the data, due to the fact that McFadden's R – squared index is equal to 57%. In addition, all coefficients of multivariate Weibull AFT model are statistically significant ($X^2(6) = 35.24$, $p < 0.01$).

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Table 7: Estimates of Weibull AFT model including factors

	Beta	**Wald statistic**
Intercept	3.12	5.10***
Wealth	-0.44	-3.69***
Economic Disparity	0.01	1.91*
Uncertainty avoidance	0.33	4.05***
Masculinity	-0.01	-0.11n.s.
Gender (Male)	-0.02	-0.02n.s
Age	0.32	1.18 n.s
Mc Fadden's R^2 (%)	**57%**	
$X^2(6)$	**35.24*** **	

***:p – value < 0.01, **:p – value < 0.05, *:p – value < 0.1, n.s.: not significant

The model exhibits exceptional fit to the data, due to the fact that McFadden's R – squared index is larger than 40% as it can be seen in Table 7. In addition, all coefficients of multivariate Weibull AFT model are jointly statistically significant ($X^2(6) = 35.24$, $p < 0.01$).

5. Discussion

E-waste is one of the most rapidly growing types of waste, created from IT products (computers, mobile phones, tablets, etc.), which significantly vary over time. This increasing trend in e-waste rejection rate depends upon a number of factors, namely, economic, demographic, and cultural. The analysis, which has been proposed so far in the extant literature, has not addressed the problem of identifying the factors that affect e-waste on a holistic basis, as the proposed analysis does. Even if e-waste increasing rejection rate is in principal a function of sales of products (computers and peripherals in this case) and lifespan, the key characteristic is the time by which the maximum rejection rate will be eventually reached. It is true that, there are many factors that either affect the maximum e-waste rejection rate negatively (i.e. delay the time at which maximum e-waste rejection is reached) or positively (i.e. accelerate the time at which maximum e-waste rejection is reached).

The methodology that has been proposed in this paper is graphically captured in Figure 4. Initially, e-waste quantities were calculated based on historical sales data and lifespan distribution. The sales data concerned computers and peripherals for leading countries from Western and Eastern Europe, North and South/Middle America, Australia/New Zealand/Japan, and Asia/Pacific regions. The most suitable distribution to approach lifespan distribution was selected based on fitting tests; the

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distribution that mostly approximates the empirical lifespan distribution was selected as lifespan distribution for the aforementioned regions. The results show that the most suitable distribution for Western and Eastern Europe, North and South/Middle America, and Australia/New Zealand/Japan is Weibull, while for Asia/Pacific is Normal.

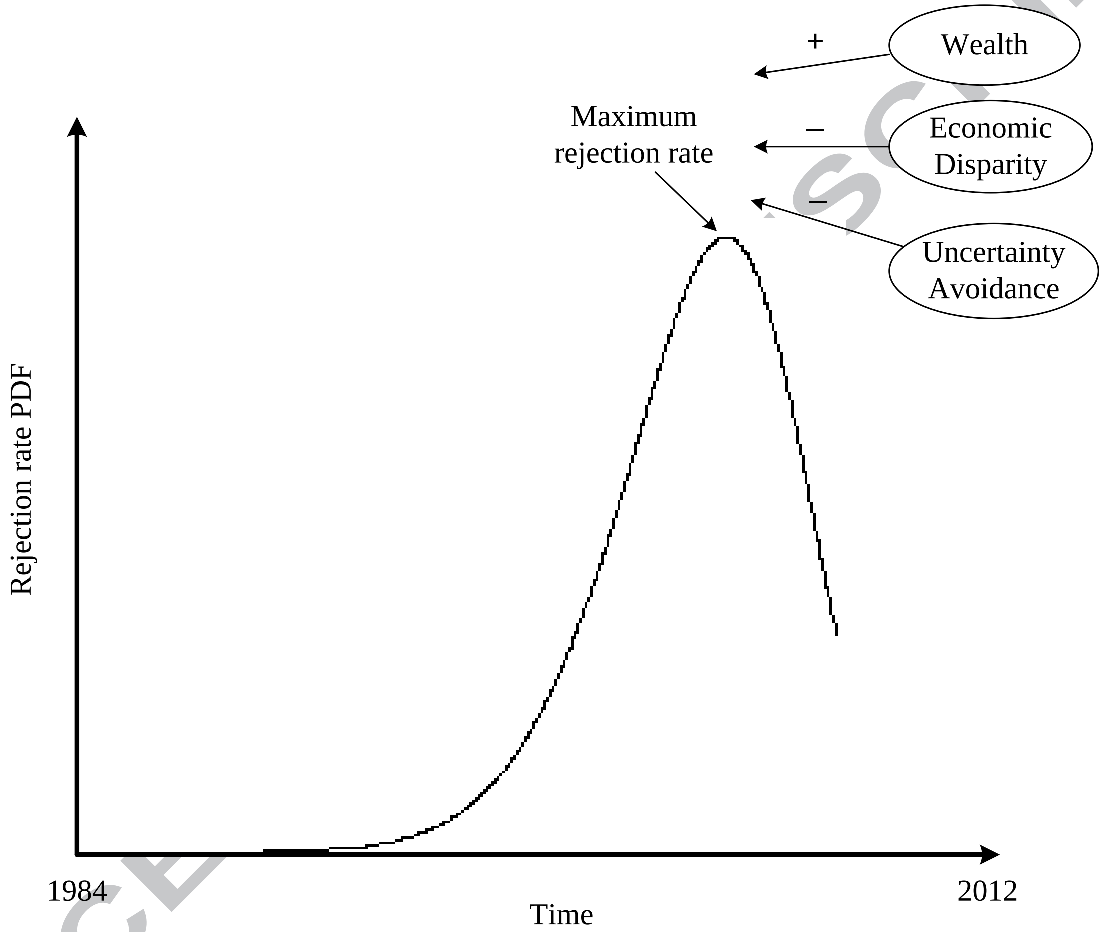

Figure 4 Graphical mapping of the proposed methodology

E-waste quantities that were calculated based on equations (1) and (2) for each country assisted in determining the time at which maximum point is achieved. After implementing Survival Analysis, and specifically applying Weibull AFT model, the factors that affect this event (maximum rejection rate of computers and peripherals) were identified. This was based on the reasonable fact that, the wealthier a country is the shorter the time the event occurs. Countries with considerable trade activities (imports, exports) seem to follow the same pattern. These results are consistent with the research hypotheses stated. From the factors, GINI coefficient along with

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consumer price index (prices) and age (dependency ratio), are associated with increasing times at which the event takes place. Due to heavily correlated explanatory variables, the inclusion in a multivariate Weibull AFT would suffer inconsistent coefficients because of multicollinearity, therefore the need to provide general constructs is imperative. Using factors analysis, two major constructs were identified: (i) "Wealth" (39% of variance explained) consisting of imports, exports, and GDP and (ii) "Economic Disparity" consisting of household size, literacy level, Internet users, and GINI coefficient.

The results derived from the estimation of Weibull AFT model indicate that: a) economic explanatory variables tend to decrease the time at which maximum rejection rate occurs, b) covariates which are associated with high order construct, i.e. media intensity, increase the time of maximum rejection rate, and c) cultural dimension and uncertainty avoidance increase the time of maximum rejection rate.

6. Decision problem example

The proposed model evaluates the time at which maximum e-waste rejection rate occurs and has obvious industrial policy implications. Based on the time – varying factors which were found to have a statistically significant effect on the time at which e-waste maximum rejection time occurs, an example for the case of USA is exhibited. Based on the statistically significant coefficients (Table 5) and considering that the difference of GDP between 1984 and 2012 ($GDP_{2012} - GDP_{1984}$) is 14.08 (measured in 10^6 million US $), the time, at which maximum e-waste rejection rate occurs, decreases by $e^{-0.27*14.08}$ = 2.23%. In addition, during 1984 and 2012 the exports of USA ($Exports_{2012} - Exports_{1984}$) increased by 1.42 (measured in 10^6 million US $), while the imports of USA ($Imports_{2012} - Imports_{1984}$) increased by 2.11 (measured in 10^6 million US $). Consequently, the time, at which maximum e-waste rejection rate occurs, decreases by $e^{-0.35*1.42}$ = 60.84% (for exports) and $e^{-0.29*2.11}$ = 54.23% (for imports). On the contrary, the dependency ratio ($Dependency\ Ratio_{2012} - Dependency\ Ratio_{1984}$) decreases by 3.5% resulting in the increase of maximum e-waste rejection rate time by $e^{0.63*(-0.035)}$ = 97.82%.

6. Policy implications

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The analysis presented in the previous sections provides significant information concerning the time at which maximum e-waste rejection rate will occur. This information is beneficial to three types of stakeholders directly affected by e-waste rejection. The first one refers to public organizations responsible for e-waste treatment and management (environmental authorities, municipalities, etc.), as well as private organizations in some cases; if they are aware of the time at which maximum rejection rate occurs, they will be able to plan their means in order to collect, transport, store, and finally recycle e-waste quantities. At corporate level, companies can give financial incentives for the return of end-of-life products, so as to achieve a balanced return policy throughout the relative time period. Similar practices have been implemented for other types of waste, such as plastic bags, glass products, etc. Finally, at governmental level a lot of developed countries tend to export e-waste quantities to a number of developing countries. In case their capacity is smaller than the forecasted quantities, they can plan appropriately their trade agreements.

7. Conclusions

E-waste consists of electrical and electronic devices (computers and their peripherals, tablets, smartphones, CD players, etc.) rejected by their owners; the reason is that either new equipment has been released in the market or the old devices have reached their lifespan. Relevant studies provide a magnitude of the size of e-waste, providing methodologies for only measuring the quantities of e-waste, leaving out several important factors. These factors that are connected with the increase of e-waste may be straightforward (e.g. economic) or not so apparent (e.g. cultural). In this paper, a model, which calculates e-waste quantities and estimates how several economic, demographic, and cultural factors affect the maximum rejection rate, is proposed. The analysis was limited only to computers and peripherals, which, however, constitute one of the most important components of e-waste. Through a Weibull AFT model, it was found that the economic factors delay the time at which maximum rejection rate of e-waste will be reached. On the contrary, cultural factors and uncertainty avoidance accelerate the time of e-waste maximum rejection rate.

The contribution of this study is the provision of a holistic framework for examining multiple factors and their impact upon the maximum rejection rate of e-waste. According to the extant literature, several factors have been individually examined,

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without investigating the direction and the extent of their impact thoroughly. Such information is useful and can be utilized by governmental authorities and other organizations in the context of optimal treatment and management of e-waste. The findings of this study provide insights about the determinant factors which accurately forecast the time of maximum e-waste rejection rate, giving the possibility to develop effective and efficient policies for sustainable e-waste operations.

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Appendix

Table I: Mean values for independent variables per country

	Internet Users	Dependency Ratio	Exports	Imports	GDP	Literacy	UAI	MAS	GINI	Prices	Gender	Households
Argentina	5866.94	61.27	25875.54	21199.11	85766.01	1786.62	86	56	44.75	92.67	0.49	9382.57
Australia	8037.14	50.28	72216.39	75293.56	581914.01	1074.19	51	61	40.99	94.57	0.50	6313.13
Brazil	27265.15	60.83	70372.42	59443.03	492732.99	3646.43	76	49	55.77	99.33	0.50	39983.82
Bulgaria	1333.70	48.36	7664.58	10847.05	14216.29	240.54	85	40	35.15	24.28	0.49	2963.01
Canada	13604.40	46.39	206268.23	191430.30	880348.52	1307.99	48	52	38.27	95.26	0.50	10532.16
China	141503.49	49.68	405922.58	354390.01	1806598.71	12469.56	30	66	42.36	81.79	0.51	309202.68
Czech Republic	3008.12	48.61	68750.56	68142.80	125441.34	293.87	74	57	26.03	100.58	0.49	4064.33
Denmark	2397.00	51.00	49528.78	45208.55	186572.15	199.52	23	16	32.80	96.86	0.49	2328.08
Estonia	479.14	50.08	6206.38	7798.24	10617.32	53.70	60	30	34.29	164.73	0.46	536.11
Finland	2409.97	49.02	38306.39	34323.24	137912.33	257.19	59	26	24.64	91.96	0.49	2152.44
France	18010.36	53.86	277572.15	301741.97	1583541.91	2064.78	86	43	33.08	93.21	0.49	22970.31
Germany	31621.91	48.21	581673.63	489393.49	2236934.91	2264.06	65	66	34.07	95.35	0.48	36117.53
Greece	1980.52	51.00	12324.84	31817.04	131381.83	355.07	112	57	38.37	88.88	0.49	3432.48
Hong Kong China	2451.02	40.95	162453.33	174244.24	121305.33	152.72	29	57	46.52	78.24	0.50	1762.11
Hungary	2466.91	49.16	32706.79	33239.64	44827.09	293.93	82	88	27.93	137.15	0.48	3890.62
Indonesia	8645.15	63.19	57420.39	43506.53	154242.86	3236.94	48	46	35.33	207.82	0.50	45309.10
Iran	4653.37	73.68	34697.92	24185.45	56151.31	1831.90	59	43	43.57	207.17	0.51	12898.31
Italy	13090.72	49.67	230571.54	233206.33	1199254.20	1833.41	75	70	36.40	90.70	0.49	21003.97
Japan	50819.77	48.30	389100.25	332113.72	4313582.68	3288.00	92	95	33.07	92.96	0.49	43547.10
Latvia	747.45	49.22	4405.44	6752.21	13055.49	92.12	36	30	34.00	143.13	0.46	803.94
Lithuania	960.40	50.74	10036.53	12624.80	21150.85	142.17	59.56	27.48	35.32	129.24	0.47	1264.47
Mexico	11587.35	71.70	116063.27	120182.43	355048.48	1793.89	82	69	50.90	149.35	0.50	20324.16
New Zealand	1807.47	53.38	14034.08	14652.52	78342.09	203.00	49	58	41.19	90.93	0.49	1232.71
Norway	2242.63	54.71	57278.33	36955.23	202354.14	1517.22	50	8	30.27	93.91	0.50	1836.51
Poland	8573.70	48.82	51649.58	57885.67	155362.66	336.03	93	64	31.32	103.45	0.49	12498.05
Singapore	1613.04	35.12	125660.46	120266.75	105635.93	131.40	8	48	45.02	95.81	0.50	913.49
Slovakia	1800.91	49.30	34415.22	35492.68	50164.14	157.43	51	100	25.93	153.09	0.49	1926.84
South Korea	19593.96	45.72	158761.77	151862.95	454523.14	2742.29	85	39	29.80	98.43	0.50	12623.09
Sweden	4348.56	55.16	79941.68	70950.93	279753.33	356.67	29	5	32.76	85.89	0.50	3841.72
Taiwan	7912.25	47.48	115292.26	102405.54	238317.50	834.31	69	45	33.03	92.10	0.51	5595.11
United Kingdom	23239.06	53.52	237833.81	296616.98	1235798.94	2027.15	35	66	34.42	91.73	0.49	23311.53
Uruguay	661.66	59.72	2564.72	3224.45	11346.86	108.64	100	38	43.17	146.43	0.49	966.20
USA	117711.39	50.91	609419.06	923399.17	8271447.22	16024.10	46	62	45.90	97.58	0.49	98717.92

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Table II: Correlation matrix of the independent variables

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Internet Users [1]	1.00											
Dependency Ratio [2]	-0.13	1.00										
Exports [3]	0.81	-0.18	1.00									
Imports [4]	0.80	-0.13	0.94	1.00								
GDP [5]	0.71	-0.03	0.79	0.90	1.00							
Literacy [6]	0.86	-0.09	0.74	0.76	0.78	1.00						
UAI [7]	-0.08	0.29	-0.10	-0.11	-0.03	-0.13	1.00					
MAS [8]	0.19	-0.14	0.28	0.26	0.29	0.19	0.30	1.00				
GINI [9]	0.24	0.16	0.19	0.22	0.20	0.33	-0.08	0.09	1.00			
Prices [10]	0.00	-0.02	-0.10	-0.10	-0.11	0.02	0.13	0.02	0.13	1.00		
Gender [11]	0.20	-0.06	0.18	0.13	0.08	0.30	-0.13	0.01	0.20	0.00	1.00	
Households [12]	0.65	-0.11	0.54	0.49	0.46	0.81	-0.18	0.21	0.26	-0.02	0.38	1.00

Table III: Descriptive statistics of the variables used

	Internet Users	Dependency Ratio	Exports	Imports	GDP	Literacy	UAI	MAS	GINI	Prices	Gender	Households
Min	0	25.3	354.5	533.8	0	24.5	8	5	19.9	0	0.4569	429.8
Q1	345.3	47.27	14580	15700	30980	205	48	39	32	56.75	0.4859	1974
Q2	2797	50.9	49650	46490	155700	749.2	59.56	52	35.6	100	0.4914	4863
Q3	12300	54.92	166000	158200	639400	2146	82	64	42.3	128.1	0.4974	21370
Max	541300	97.8	2050000	2276000	16160000	32590	112	100	61.5	985.8	0.5234	432000
Mean	16700	52.09	139600	143900	819200	1990	61.59	50.83	36.92	108.5	0.4911	23160

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Highlights

- Factors affecting positively or negatively e-waste rejection rates are examined.
- Economic, cultural, demographic factors are considered.
- Weibull Parametric Accelerated Failure Time model is applied.
- E-waste rejection rate is prolonged by economic disparity and cultural variables
- Wealth causes a shorter time of rejection rate

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